Impervious Cover Analysis for the Saluda-Reedy Watershed in Upstate South Carolina

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Abstract

Using the amount of impervious surface cover within a watershed has gained attention as one of the strong emerging indicators of water quality. Several methods to estimate and quantify impervious surfaces have been devised and applied in the past. Accurate spatial data on urban land-cover and land-use is a necessary element to support urban land management decision-making, ecosystem monitoring and urban planning. This study examines the role of impervious surfaces as an indicator of water quality in the Saluda-Reedy Watershed of upstate South Carolina. An integrative application of Geographic Information Systems and satellite remote sensing techniques using Normalized Difference Vegetation Index (NDVI) is explored to estimate the amount of impervious cover for four annual time periods spanning fifteen years. This technique, while potentially underestimating total cover was deemed preferable to other analytical techniques like unsupervised land-cover classification (which potentially overestimates impervious cover) and hyperspectral remote sensing (which proved too expensive to provide complete coverage of the study area). Water quality data corresponding to the chosen time periods was gathered and statistically tested for examining correlations with amount of estimated impervious cover. This research offers valuable contributions in the subject of impervious surface mapping using commercially available Landsat TM satellite imagery. An accurate estimation of impervious surface area in a region will provide clues to local and regional governments for revising planning and zoning ordinances, laws and procedures in order to create sustainable communities with a healthy natural resource base.

Introduction

Impervious cover refers to surfaces which prevent infiltration of water into the soil. Roads and rooftops being the major contributors to the total impervious area, parking lots, pavements, sidewalks and compacted soil constitute other types. In undeveloped regions, storm water filters down through the soil, replenishing ground water quantity with water of good quality (Kauffman and Brant 2000). Prevention of water permeability into the ground disrupts the water cycle by altering natural hydrologic patterns. Dominance of impervious surfaces in the landscape also results in increased concentration of storm water flow causing stream channel erosion, habitat degradation and severe impairment of aquatic communities (Bird et al. 2002). Thus, the increase of impervious surfaces is directly attributable to human habitation and construction activity. The quantity of these surfaces has proved to be a valuable indicator of the intensity of urban development (Arnold and Gibbons 1996). The imperviousness issue has also been suggested as a unifying theme for overall study of watershed protection (Schueler 1987, 1994) and as an urban ecosystems analytical model (Ridd 1985, 1995).

Quantifying and analyzing impervious surfaces is an important step for determining the current state of a watershed. It can serve as a key ingredient to carry out further research for determining land-use planning implications and directing future decision-making processes for ecologically sensitive zones. This study is undertaken with an aim to provide impervious cover datasets for the South Carolina Water Resource Center, which is currently conducting research as a part of the Saluda Reedy Watershed Consortium. The consortium is a collaborative effort by organizations and individuals concerned in part about the impacts of changing land-use on the purity and abundance of water in the Saluda-Reedy basin.

Many approaches have been developed by various agencies for mapping impervious surface. The USGS methodology, possibly the most commonly used and referenced, involves multiple regressions (Forster 1980; Ridd 1995), spectral mixing (Ji and Jensen 1999; Ward et al. 2000), artificial neural networks (Wang 2000; Flanagan and Civco 2001) and classification trees (Smith et al. 2003; Yang et al. 2003). The study team considered numerous methodologies for deriving impervious cover for a given geography. Three approaches in particular appeared promising including: 1) a multi-scale strategy developed by the U.S. Environmental Protection Agency using the National Landcover Data from 1992 and 2001; 2) the Impervious Surface Analysis Tool developed by the National Oceanic and Atmospheric Administration; 3) a land cover coefficient method developed through the Non-point Education for Municipal Officials in Connecticut. Because of data constraints and other problems, none of these three approaches were deemed appropriate for the SRWC study area.

Other analytical techniques considered included unsupervised land-cover classification from satellite imagery (Yang et al. 2003; Yang and Lo 2002) and airborne hyperspectral remote sensing (which proved too expensive to provide complete coverage of the study area). The land-cover classification from Landsat Thematic Mapper satellite imagery potentially confuses impervious cover with other land classes like “developed”, “built”, and “urban/suburban”. At issue are tens of thousands of cells scattered across the landscape identified as "developed" that may indeed be impervious surface (e.g. asphalt of a road through the country or forest) but should really not be considered "developed" or "urban" for other analytical purposes, for anything else but literally "impervious surfaces." In addition, USGS has initiated including impervious cover data with Landsat imagery starting in the year 2000. While this is helpful for some analyses, there is no data available for prior time periods studied (1985, 1990, 1995) and therefore makes the data sets temporally incompatible. Appendix A provides additional information regarding the satellite land cover classification and the hyperspectral remote sensing.

Methodology

Watersheds for this study are categorized as hydrologic unit codes (HUC) which are nationally consistent delineations of hydrologic boundaries associated with major U.S. river basins. The U.S. Geological Survey hydrologic unit hierarchy consists of 21 regions, 205 sub-regions, 336 accounting units and 2,104 cataloging units. The cataloging unit requires four pairs of two digit numbers as its unique HUC – referred to as an 8-digit HUC. Watersheds and sub-watersheds require an additional three digit number for identification. For example, the study area is part of the Saluda River basin in South Carolina which is identified with the 8-digit HUC code of ‘03050109’. Several smaller watersheds within the basin are identified as an 11-digit HUC code. The North Saluda River watershed within the Saluda River basin is expressed as ‘03050109-010’. All of the impervious surface analysis for this study was conducted at the 11-digit HUC code.

The methodology used for this study was primarily based on Normalized Difference Vegetation Index (NDVI). NDVI is an index that provides a standardized method of comparing vegetation greenness between satellite images (Wang et al 2005, Cooke and Jacobs 2002, Gupta et al 2000). Historically this method has been developed and researched upon for mapping density of green vegetation on large regional and even continental/global scales. In this research, the project team utilized cells with low NDVI values as resulting low greenness values which thereby correspond to cells with potential impervious characteristics.

The greenness values for NDVI are derived after running an index over the satellite image of the study area and are interpreted as impervious areas encountered in our built and un-built environment. This method was proposed in 1973 by Rouse et. al. as a simple algorithm to process data and locate the distribution of vegetation on the great plains, and remains as the most well-known and used index to detect live green plant canopies in satellite data.

When sunlight strikes an object, certain wavelengths of this spectrum are absorbed and other wavelengths are reflected. The pigment in plant leaves chlorophyll, strongly absorbs visible light (from 0.4 to 0.7 um) for use in photosynthesis. The cell structure of the leaves however, strongly reflects near infrared light (from 0.7 to 1.1 um) Thus, the more leaves encountered the more these particular wavelengths of light are

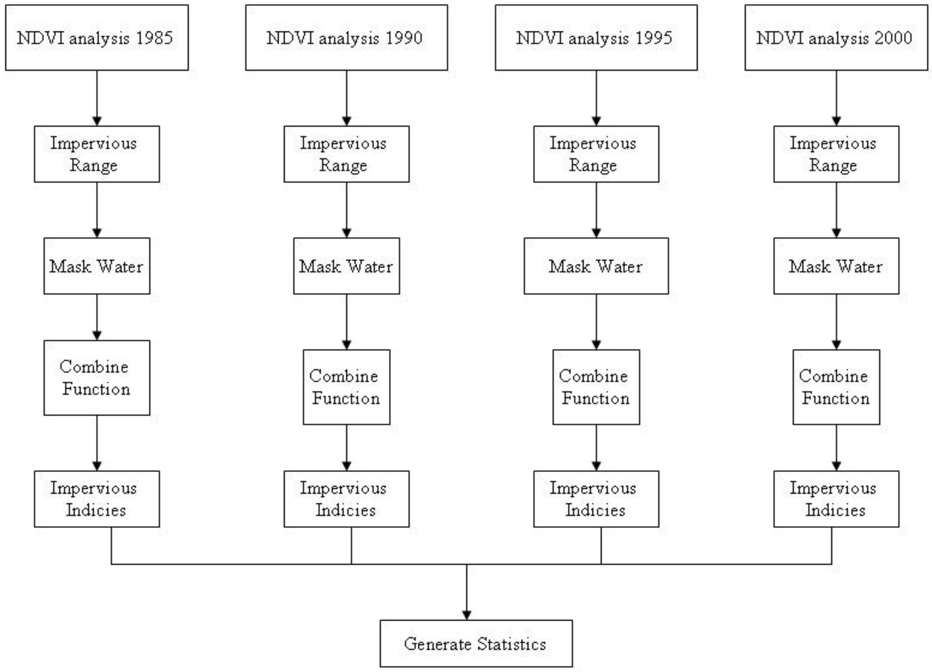


Figure 1: Methodology used for Impervious Surface Analysis

affected. In technical terms, NDVI is defined as the difference between the visible (red) and near-infrared (NIR) bands, over their sum –

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Where, RED and NIR stand for the spectral measurements in the red and near-infra-red regions respectively. These spectral reflectances are ratios of the reflected over the incoming radiation in each spectral band. They therefore are expressed as values between 0.0 and 1.0. The NDVI varies between the values -1.0 to +1.0. Very low values of NDVI (0.1 and below) typically correspond to barren areas of rock, sand and/or man made structures and surfaces. In other words, low NDVI values describe presence of materials with characteristics exactly opposite to those containing chlorophyll – possibly

asphalt paved roads and parking lots, rooftops and sidewalks and other surfaces comprised of man-made materials. Moderate NDVI values represent shrub and grassland (0.2 to 0.3), while high values represent thick vegetated, forested zones. (0.6 to 0.8). Figure 1 shows the process of analysis conducted for this project.

NDVI analysis was conducted in Erdas Imagine software using the Spectral Enhancement tab in the main Interpreter menu. The input data for this function was raw satellite image from each of the years chosen for study. Raw NDVI raster results after applying this function with 14 Digit-HUC watersheds delineated are illustrated above. It should be noted that the NDVI values range from -1 to +1, except for the year 1985 where the values ranged from -1 to +0.75. On further examination it was found that the values for water, and developed areas (impervious surface zones) coincided with each other. This would imply that if this result was to be quantified in terms of impervious acreages, (which was the intended final result) the values of water would get counted in addition to impervious areas. The next step thus involved masking out the water from the raw NDVI rasters.

Table 1: Translation of NDVI range into imperviousness range

	Imperviousness	Values	NDVI Interpretation	
		-1		
		-0.9		
		-0.8		Low
High		-0.7		
		-0.6		
		-0.5		
	High Imperviouness (Water masked out)	-0.4	Barren areas of rock/sand/ water	
		-0.3		
		-0.3		
		-0.2		
		-0.1		
		0		
		0.1		
		0.2		
	Medium Imperviousness	0.3	Shrubland/grassland/ compact soil	
		0.4		
Low		0.5		High
		0.6		
	0.5 to 1 Low imperviousness	0.7	0.5 to 1 High Vegetation	
		0.8		
		0.9		
		1		

Performing the task of masking water out of the NDVI rasters was accomplished by exploring ArcGIS's spatial analysis capabilities. The "Combine" function provides for the assemblage of multiple rasters to give a unique output value. A class is assigned to every unique combination of input values.

The ArcGIS "Combine" function works only with integer values. Hence each NDVI raster was processed to provide values in whole integers instead of the default decimal values. This step was done in Erdas Imagine Modelbuilder. A function of NDVI raster x * 100 was applied to convert decimals values into integers. The resulting raster thus gave values from -100 to +100 (-100 to +75 in case of 1985 NDVI) as compared to the original values of -1 to +1.

In order to separate values for water and impervious areas, a raster containing only water values had to be combined with the NDVI integer raster. The National Land Cover Dataset (NLCD) prepared by the MRLC Consortium (Multi-resolution Land Characteristics Consortium) and supplied by the USGS meets the need for nationally consistent satellite remote sensing and land cover data. The NLCD 1992 layer was reclassified to give the resulting two values – water class, and non-water class. This layer was used as the second input to the NDVI integer raster for executing the Combine function in ArcGIS spatial analyst.

The following figure 2 illustrates the appearance of the raster images before and after the process of applying the Combine function. Interestingly, the nature of the NDVI raster of having higher values for vegetation and lower values for impervious area reversed significantly after it was combined with the water raster. The pattern of distinct developed areas although, was consistent. Investigating into this apparent inverse relationship of the raster was outside the scope of this study.

Figure 2: NDVI Raster after executing Combine and NDVI Integer raster (Year 1989)

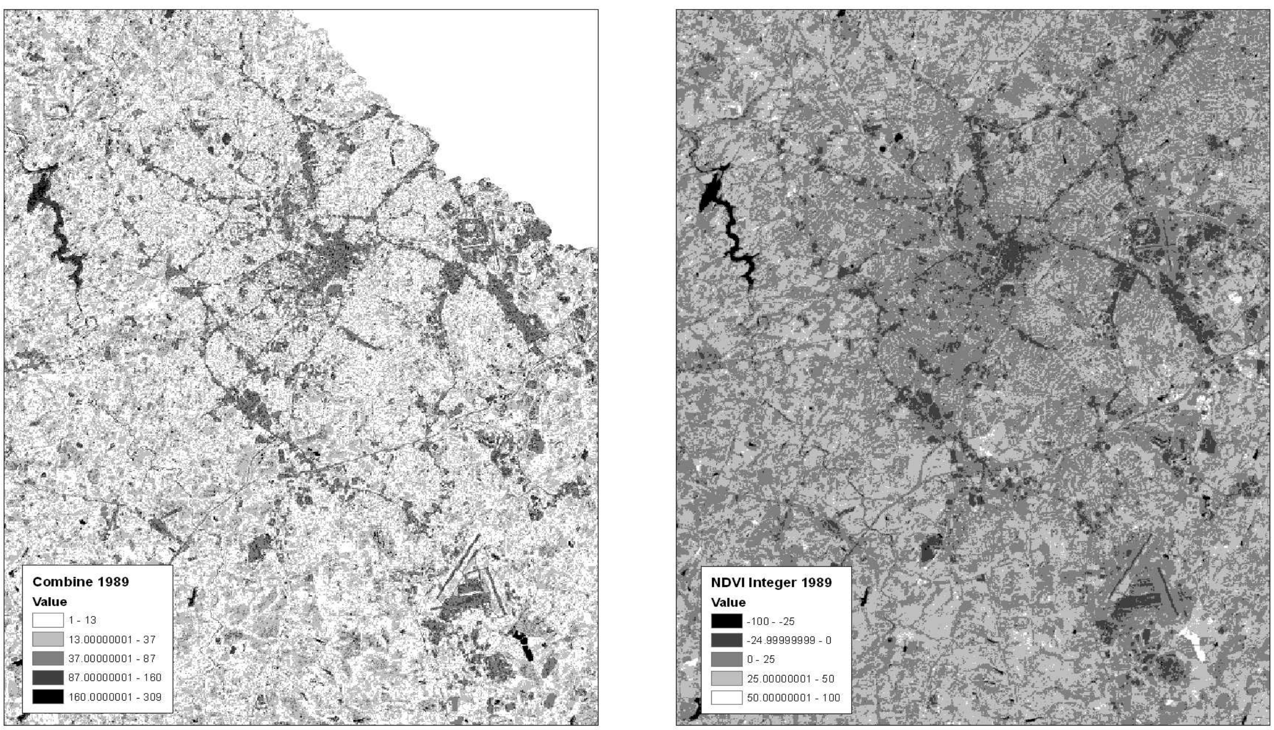


Table 2: Differences between NDVI integer raster and combine raster

NDVI Interpretation	NDVI Integer Value	ArcGIS Combine value	Combine Interpretation
Impervious	-100	1	Vegetation
	to	to	
Vegetation	100	309	Impervious

The table given below illustrates how the water class was separated from the NDVI integer raster using the Combine function. Value 2 in the water raster corresponded to water class.

Table 3: Separating water class from NDVI raster

Raster 1 NDVI Integer	Raster 2 NLCD Water	Reclass of Combine Raster Result value
x	1	Low / Medium /High /Very High Impervious
y	2	0 – Water Class

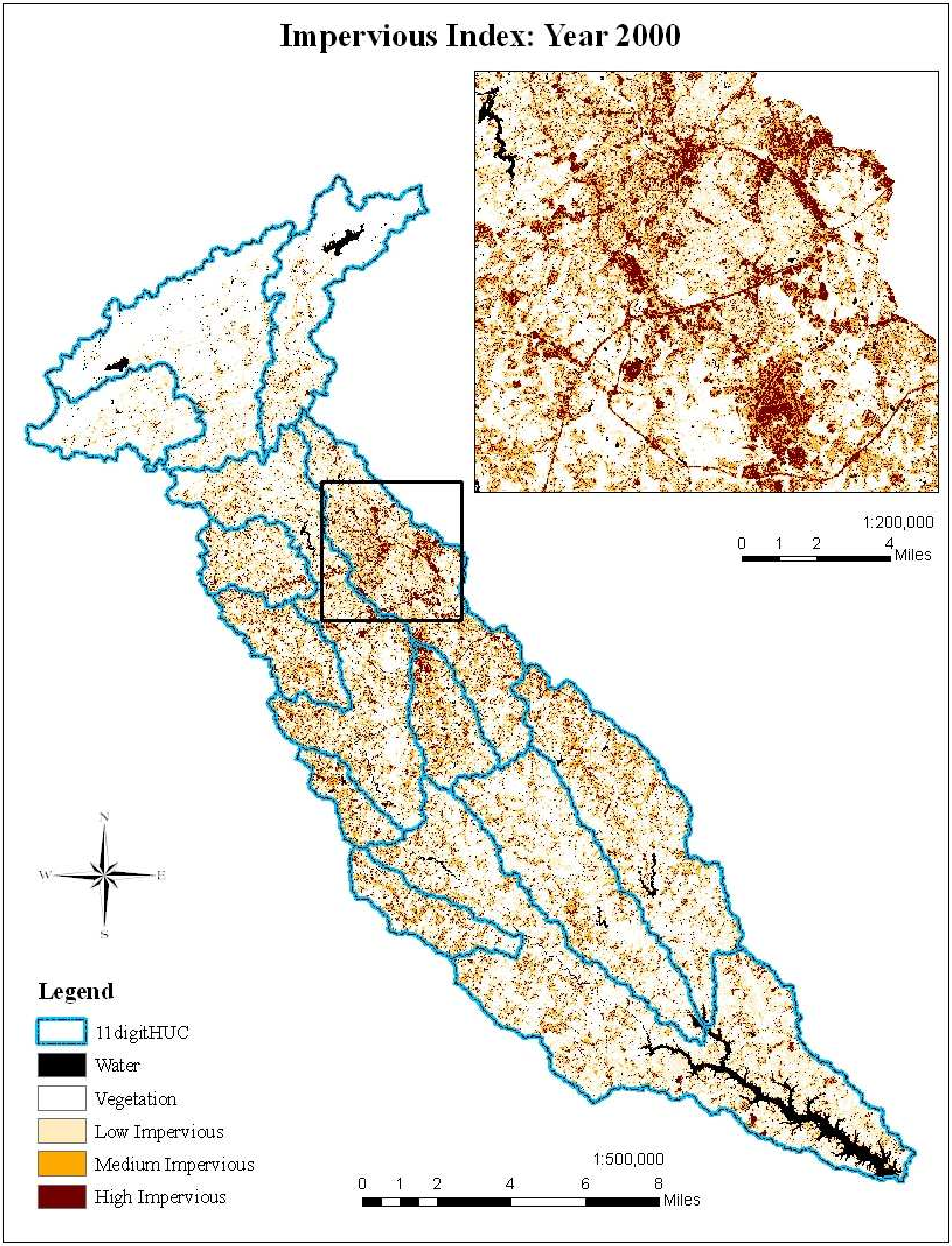
Table 4: Imperviousness breakup values for each time-period

Classification Break-up Values	1985	1989	1995	2000
Low Impervious	1 to **11**	1 to **15**	1 to **17**	1 to **27**
Medium Impervious	12 to **43**	16 to **59**	18 to **71**	28 to **79**
High Impervious	44 to **111**	60 to **125**	72 to **145**	80 to **135**
Very High Impervious	112 to **236**	126 to **309**	146 to **314**	136 to **349**

Imperviousness Indices

Imperviousness indices for each of the time-periods as obtained with the above given break-up values are provided below. It should be noted that certain discrepancies in the levels of imperviousness may be found on comparison of indices.

Figure 3: Imperviousness index – Year 2000



NDVI integer rasters for each time-period were reclassified into 7 classes per break-up values. Obtaining spatially clustered pixels per class was the determining factor for break-up values. Each level break-up was assigned a common impervious class as given in the following table. Zonal statistics calculated mean percent values of imperviousness for each time-period. For ease in understanding and explanation, the classes are described in terms of percent values. It should be noted that giving actual percent imperviousness values requires calculation of 'imperviousness coefficients', which give a logical reasoning to the percent value associated with each class.

Table 5: Value raster class break-up values for calculating zonal statistics

Imperviousness	**2000**	**1995**	**1989**	**1985**
0 to 10%	88 to 66	52 to 92	27.1 to 89	18 to 70
80% to 100%	-4 to -7	2 to 12	-22	10 to 18
60% to 80%	8 to 18	12 to 25	-16	6 to 10
40% to 60%	18 to 36	30 to 40	-8	1 to 6
20% to 40%	37 to 56	40 to 52	-2	-6.9 to 1
10% to 20%	56 to 65	52 to 92	-5	-16.9 to -7
0 to 10%	-80 to -4	-100 to -10	-74 to -10	-50 to -17

The map given on the following page illustrates resulting rasters for all time-periods. Maximum impervious value in 1985 was 17.82%, which in 1989 increased to 20.40%. This value further increased to 22.79% in 1995 and finally to 33.05% in the year 2000. According to Schuler (1994), a watershed is

- sensitive – at <10% imperviousness,
- impacted – at >10% - 25% imperviousness and
- degraded – at >25% imperviousness.

The maps indicate that in 1985 only one watershed of the thirteen in the Saluda-Reedy basin was clearly impacted while six other watersheds were at the early stage of impact. By 1989 ten watersheds contained enough impervious cover to be considered impacted. In 1995 ten of the watersheds were determined to be impacted by impervious cover though the arrangement of the ten was slightly different than 1989. By 2000 three of the watersheds stayed in the sensitive category while four of the watersheds were in the impacted category and six of the watersheds moved into the degraded category with the Reedy River (city of Greenville) watershed having the highest percentage of impervious cover.

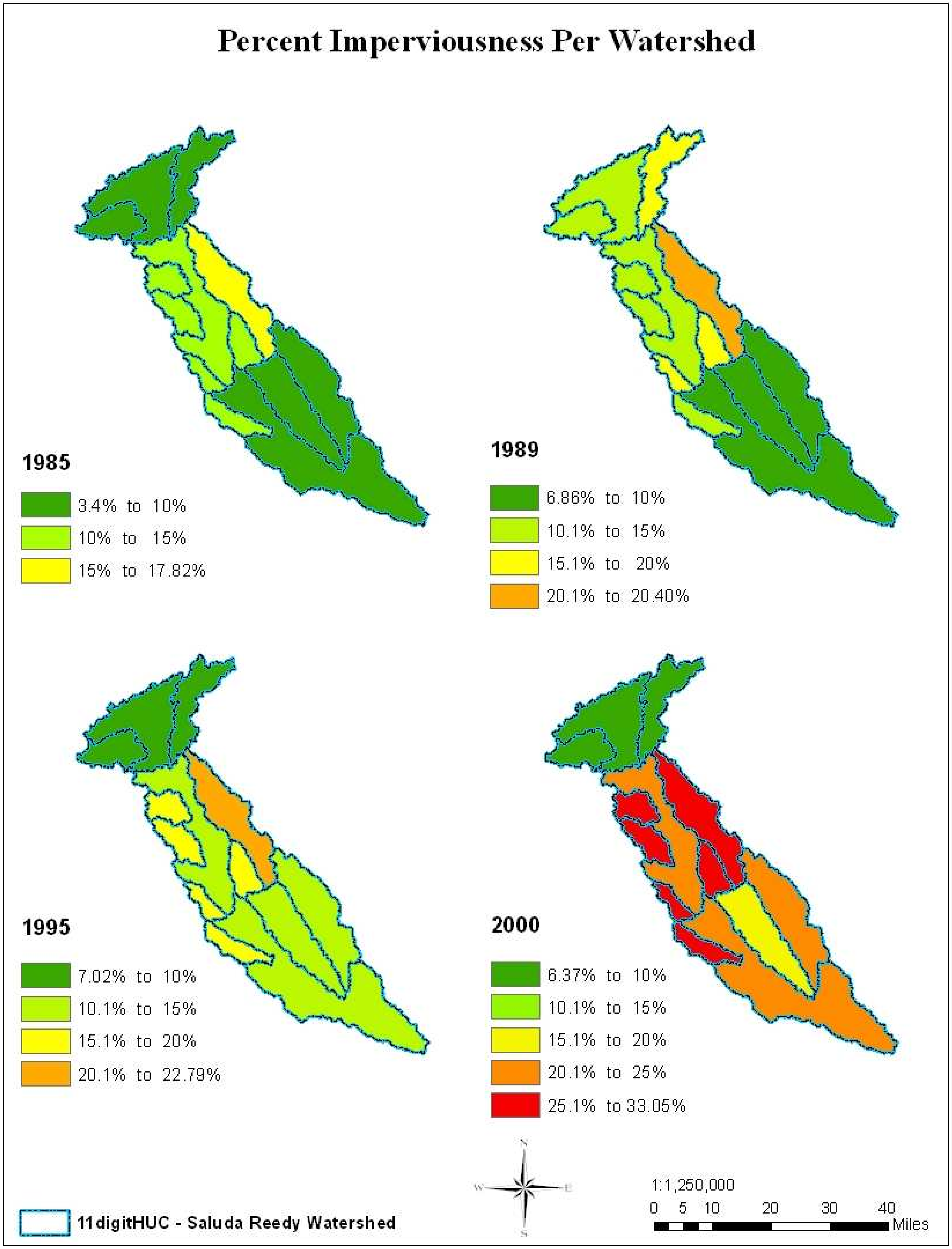


Figure 4: Percentage imperviousness per watershed for all time-periods

Table 6: Areas of impervious cover in individual watersheds compared to the original classified urban classes, Year 1985

Watershed	Imperviousness 1985	Original Urban Classified 1985
	Sq Miles	Sq Miles
North Saluda River watershed 010	1.721	2.534
South Saluda River watershed 020	1.998	1.861
Oolenoy River watershed 030	0.471	0.855
Saluda River watershed 040	3.064	17.372
Big Creek watershed 050	0.876	3.496
Georges Creek watershed 060	0.897	6.045
Big Bushy Creek watershed 070	0.345	3.563
Saluda River watershed 80	7.749	19.68
Broad Mouth Creek watershed 090	0.648	4.327
Reedy River watershed 100	6.424	32.346
Huff Creek watershed 110	1.177	5.715
Reedy River watershed 120	1.614	9.071
Rabon Creek watershed 130	2.113	13.268

Table 7: Areas of impervious cover in individual watersheds compared to the original classified urban classes, Year 1990

Watershed	Imperviousness 1990	Original Urban Classified 1990
	Sq Miles	Sq Miles
North Saluda River watershed 010	1.620	5.598
South Saluda River watershed 020	2.562	7.851
Oolenoy River watershed 030	0.892	3.629
Saluda River watershed 040	8.783	28.071
Big Creek watershed 050	2.485	6.41
Georges Creek watershed 060	2.764	10.035
Big Bushy Creek watershed 070	1.359	5.459
Saluda River watershed 80	17.701	35.234
Broad Mouth Creek watershed 090	2.779	6.881
Reedy River watershed 100	17.378	40.493
Huff Creek watershed 110	3.225	9.078
Reedy River watershed 120	4.542	14.84
Rabon Creek watershed 130	6.794	19.768

Table 8: Areas of impervious cover in individual watersheds compared to the original classified urban classes, Year 1995

Watershed	Imperviousness 1995	Original Urban Classified 1995
	Sq Miles	Sq Miles
North Saluda River watershed 010	3.191	7.319
South Saluda River watershed 020	2.857	8.979
Oolenoy River watershed 030	1.414	4.076
Saluda River watershed 040	10.025	33.486
Big Creek watershed 050	2.427	8.864
Georges Creek watershed 060	2.963	11.699
Big Bushy Creek watershed 070	1.573	5.255
Saluda River watershed 80	16.143	33.148
Broad Mouth Creek watershed 090	2.543	6.012
Reedy River watershed 100	17.844	49.84
Huff Creek watershed 110	3.695	8.765
Reedy River watershed 120	5.525	13.346
Rabon Creek watershed 130	8.279	19.112

Table 9: Areas of impervious cover in individual watersheds compared to the original classified urban classes, Year 2000

Watershed	Imperviousness 2000	Original Urban Classified 2000
	Sq Miles	Sq Miles
North Saluda River watershed 010	3.800	10.993
South Saluda River watershed 020	4.228	13.328
Oolenoy River watershed 030	8.706	7.362
Saluda River watershed 040	31.889	38.676
Big Creek watershed 050	7.383	10.104
Georges Creek watershed 060	11.469	13.453
Big Bushy Creek watershed 070	6.987	5.072
Saluda River watershed 80	43.313	36.044
Broad Mouth Creek watershed 090	9.369	6.801
Reedy River watershed 100	36.615	65.79
Huff Creek watershed 110	13.159	9.593
Reedy River watershed 120	18.149	13.538
Rabon Creek watershed 130	29.080	19.725

Conclusion

One of the goals of this study was to map and estimate impervious surface cover in the Saluda-Reedy River basin with the aid of remote sensing and geographic information systems techniques. Commercially available moderate spatial resolution (30m x 30m ground cells) Landsat Thematic Mapper satellite imagery for the years 1985, 1989, 1995 and 2000 was obtained from the U. S. Geological Survey. An integrative application of geographic information systems and satellite remote sensing techniques using Normalized Difference Vegetation Index (NDVI) was explored to estimate the amount of impervious cover for four annual time periods spanning fifteen years. This technique, while potentially underestimating total cover was deemed preferable to other analytical techniques like unsupervised land-cover classification and hyperspectral remote sensing. The unsupervised land-cover classification, while commonly used to derive various land covers (including developed land), potentially overestimates impervious cover by assigning areas that may contain only a small fraction of development to the developed class. The hyperspectral remote sensing techniques, while potentially providing detailed and highly accurate impervious surface classification, contained extensive error in the raw imagery (which was too difficult to rectify) and proved too expensive to provide complete coverage of the study area).

A significant increase in impervious cover acreage was observed over each of the time periods of satellite image analysis; 1985, 1989, 1995, and 2000. The percentage of imperviousness was also estimated and compared to a watershed scale health index to give an indication of potential water quality problems in each of the watersheds within the larger Saluda-Reedy basin. Starting in the study year 1985, only one watershed (Reedy River watershed including the city of Greenville) with an impervious value of 17.82% was above the initial degradation threshold of 10%. By the year 1989 the impervious value for the Reedy River watershed had increased to 20.4%. The value increased further to 22.79% for the study year 1995. The most significant change and increase in imperviousness is seen in the year 2000. For that study year ten of the thirteen watersheds crossed the threshold of impacted (10% imperviousness) with three of the watersheds staying in the sensitive category while four of the watersheds were in the impacted category and six of the watersheds moved into the degraded category with the Reedy River (city of Greenville) watershed having the highest percentage of impervious cover of 33.05% and the highest potential degradation.

The research from this study highlights the percentage of impervious surface within each 11-digit HUC watershed of the Saluda-Reedy basin. While the index maps showed increases of imperviousness throughout the fifteen year study period it should be noted that some discrepancies (for example GSP airport falls under different impervious categories in 1989 and 1995 even though the amount of impervious surface did not change) do occur and that with more time and resources the index should be tested for accuracy using ground-truthing of high resolution aerial imagery or other techniques. Also, percent imperviousness was a direct percentage calculated from NDVI rasters which deviated from “imperviousness coefficients” calculated in past studies. Further research is needed to determine which methodology is the more accurate.

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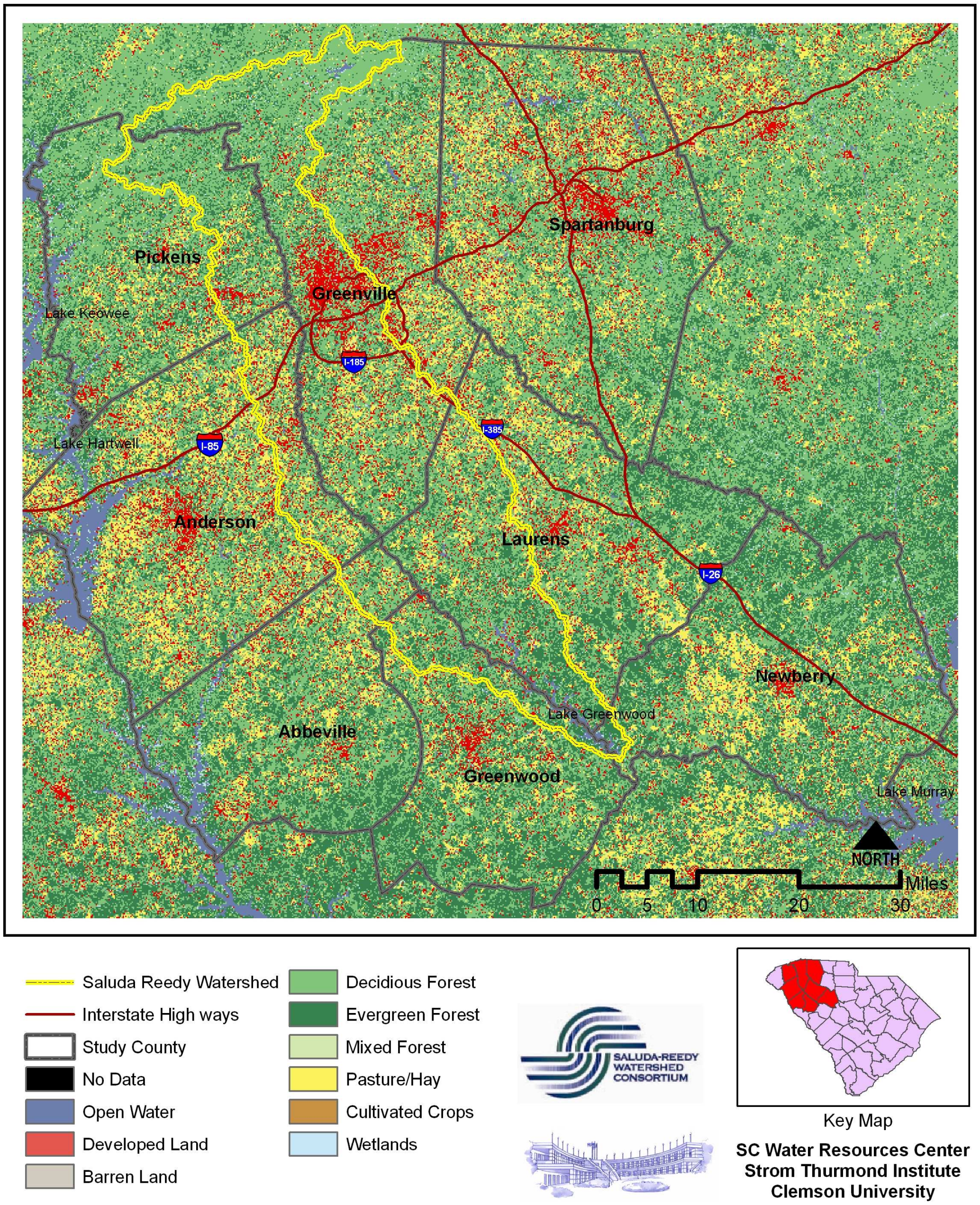
Appendix A

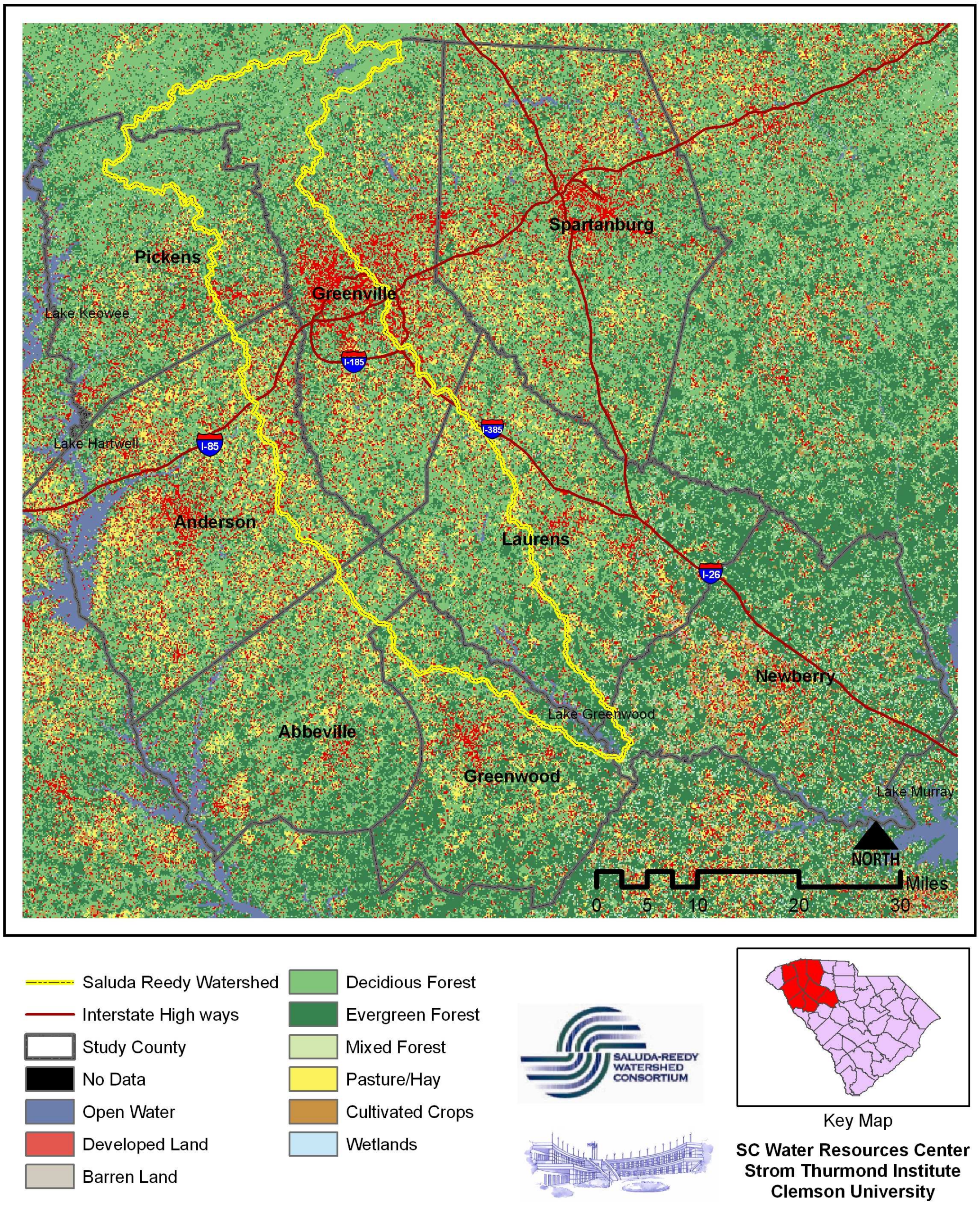
Land Cover as a Measure of Impervious Surface
1985, 1990, 1995, 2000

Saluda Reedy Watershed Consortium
Land Cover Classification -Year 1985

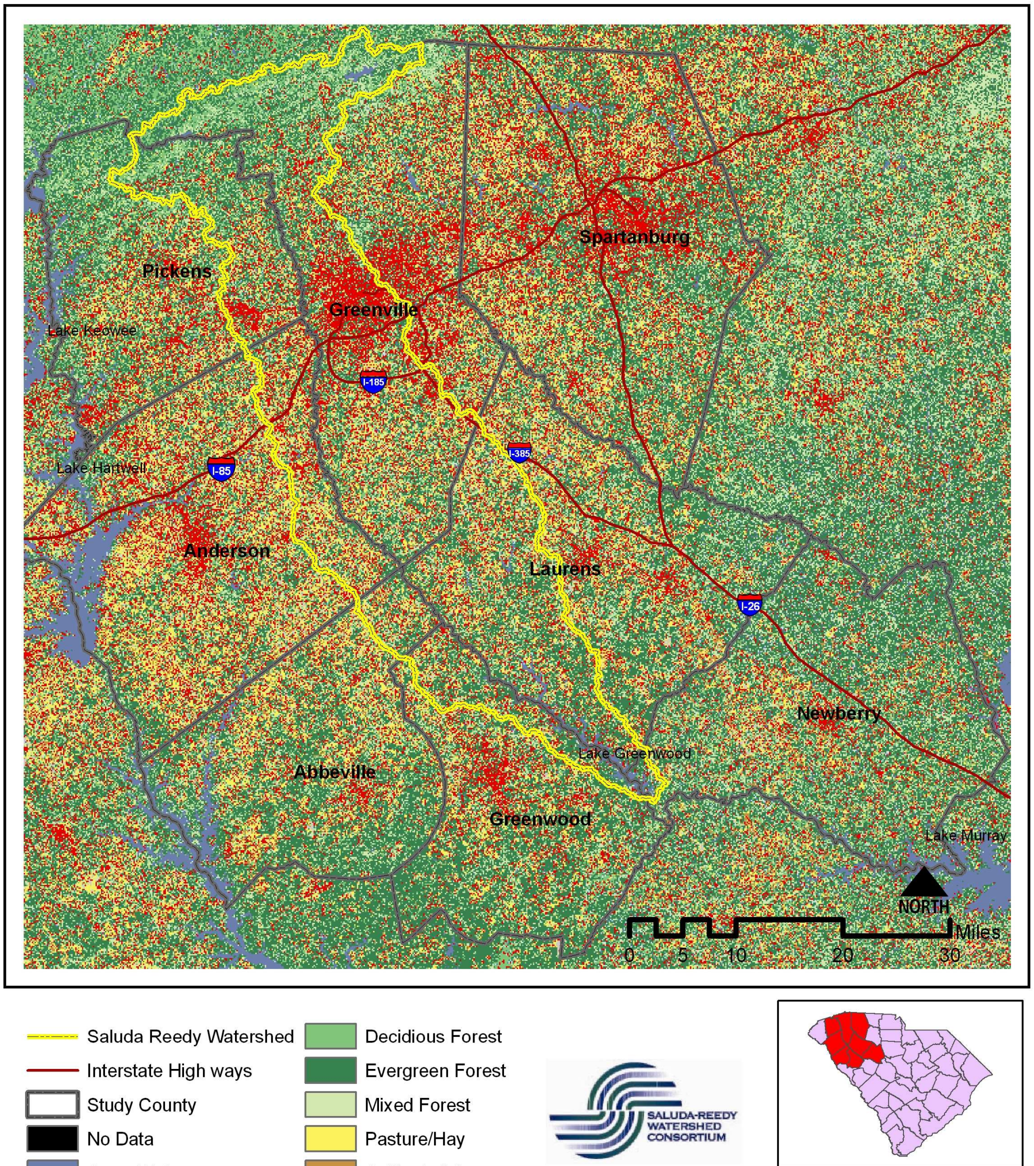


SC Water Resources Center
Strom Thurmond Institute
Clemson University

Saluda Reedy Watershed Consortium
Land Cover Classification -Year 1990



Saluda Reedy Watershed Consortium
Land Cover Classification -Year 1995



SC Water Resources Center
Strom Thurmond Institute
Clemson University

Saluda Reedy Watershed Consortium
Land Cover Classification -Year 2000